# Social networks and the labour market mismatch

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## Abstract

This paper assesses the extent to which social contacts and ethnic concentration affect the education-occupation mismatch of natives and immigrants. Using Australian panel data and employing a dynamic random effects probit model, we show that social capital exacerbates the incidence of over-education, particularly for females. Furthermore, for the foreign-born, ethnic concentration significantly increases the incidence of over-education. Using an alternative index, we also show that social participation, friends and support and ethnic concentration are the main contributors in generating a mismatch, while reciprocity and trust does not seem to have any effect on over-education for both, immigrants and natives. Finally, we show that social networks are more beneficial for the relatively better educated.

Keywords: social capital, ethnic concentration, over-education

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## 1. Introduction

Individuals seeking employment use a variety of different job search methods to enter the labour market. These include contacting employment agencies, searching through newspaper or website advertisements, approaching employers directly and, most importantly, using personal networks such as friends and relatives. Considerable research has been conducted on the significance of the role personal networks (or social capital) play on an individual's labour market outcome, as these networks provide them with useful information about the job market and improve their chances in finding employment.

Social capital is generally defined as the social relations and social networks of individuals, which can be characterised by norms of trust and reciprocity leading to outcomes of mutual benefit (Bourdieu 1993; Coleman 1988; Putnam 1993).[1] Although a large body of theoretical and empirical work shows that social contacts could help individuals enter the labour market,[2] there is limited research that focuses on what type of jobs individuals get. More precisely, friends and relatives may play a significant role in helping individuals find employment, but it does not necessarily mean that the job found through social networks matches an individual's education level.

When analysing the labour market performance of job seekers, a common problem emphasised in the literature is the existence of education-occupation mismatch. This phenomenon has been widely studied in the literature emphasising on the determinants as well as the consequences of mismatch and the importance of the potential wage loss individuals experience in the labour market (see Hartog, 2000; McGuinness, 2006; Leuven and Oosterbeek, 2011; Piracha and Vadean, 2013; Nielsen, 2011). However, limited research exists assessing the link between social capital and over-education.

Social capital can either reduce the possibility of labour market mismatch or it could possibly accentuate the effect. On the one hand, social capital, much like human capital, plays an important role in the labour market and could help individuals obtain

[1] For a general discussion, see Winter (2000).
[2] See for instance, Calvo-Armengol and Jackson (2004, 2007), Calvo-Armengol and Zenou (2005), Wahba and Zenou (2005).

employment that matches their qualifications. On the other hand, however, it may only provide an imperfect, and perhaps temporary, solution for job seekers to avoid the 'stigma' of unemployment. For instance, if individuals have remained unemployed for a long period of time and experience financial difficulties, they are likely to accept jobs that require a lower level of education than the one formally obtained. In that case, even if social capital makes a positive contribution in facilitating access to the labour market, it may in fact generate a mismatch.

Using data from the Households Income and Labour Dynamics in Australia (HILDA), we analyse whether social capital can help the job seekers – natives and immigrants – in finding an occupation that matches their level of education.[3] The HILDA survey provides rich information about individuals' dynamics of employment status and education level as well as questions related to social networks and social relations in Australia. We capture social capital by utilising two different methods. The first one is an index, constructed using principal component analysis (PCA), of several aspects of social capital including amount of support, frequency of contact with friends and family, feeling part of the community and social participation. The second, "alternative measure" uses three separate indices – 'social participation', 'reciprocity and trust' and 'friends and support'. The idea of the alternative measure is to assess the sensitivity among different 'types' of networks. Finally, for the immigrant sample only, we also consider the role of ethnic concentration.

Panel data estimation techniques are used to examine the dynamics of mismatch (over- and under-education) as well as the causal effect of social capital on the incidence of a possible mismatch, controlling for state dependence, initial conditions problem and unobserved individual heterogeneity. In addition, Mundlak corrections have been used in order to control for unobserved time-invariant individual heterogeneity of the variables of interest. The results show that social capital has a statistically significant and positive effect on the probability of being over-educated, i.e., it exacerbates the incidence of over-education, while no significant effect of social capital is observed on the incidence of being under-educated. In addition, immigrants experience worse labour market outcomes when residing in regions with

[3] Using the same data set, Green *et al* (2007) show that immigrants in Australia are much more likely to be overeducated than the natives and the difference is more pronounced for those coming from non-English speaking backgrounds.

higher proportions of ethnic concentration. Significant gender differences are also observed where social capital and ethnic concentration appear to worsen the mismatch for females, while no effect is observed for the male sample. When using alternative measures of social capital and distinguishing between levels of education, the results suggest that social participation and friends and support are likely to act as important contributors in reducing over-education for the relatively more educated, while those with lower levels of education do not seem to benefit from their contacts.

## 2. Social capital and the labour market

The quality and structure of social networks have been widely recognised to play a significant role for the achievement of specific economic outcomes in the labour market. A number of studies have found that social networks can lead to economic opportunities, efficient transactions and ultimately to economic growth as they allow people to 'leverage on resources' such as knowledge and information of members in the network (Lin, 1999; Mouw 2003; Ioannides and Loury, 2004). The positive role of social capital on individuals' labour market outcomes has been the subject of considerable research, with a growing interest by economists to study the impact of social networks on labour market outcomes in terms of employment entry and wages.[4] Several factors have been proposed in the literature that are linked to social capital such as social and civic participation, social networks and social support, reciprocity and trust as well as subjective views about the locale where one lives. The three main aspects of social capital commonly referred to in the literature are 'bonding' 'bridging' and 'linking' (Putnam, 2000). 'Bonding' refers to social contacts with close friends and relatives while 'bridging' refers to casual contacts such as colleagues and more distant friends. Finally, 'linking' refers to the interaction people have with others through social participation and memberships of a club or association, voluntary activities as well as the participation of political and educational organisations. One key finding in the literature is that 'weak' ties have a more significant impact on finding a better job than do 'strong' ties. Strong ties are associated with social contacts and resources within an individual's own network (Barbieri 2000; Lin 1999), while weak ties are classified as contacts individuals have in networks that are distant from the individual's own network (e.g., individuals living

[4] For a general literature review on the role of social networks in the labour market see Ioannides and Loury (2004).

in rural areas having contacts with persons living in cities). The benefit from more distant network comes from the fact that one has access to information and resources not available within one's own network.[5] For instance, using a theoretical model, Granovetter (1973) argues that weak ties increase individuals' economic outcomes as they provide them with information and resources of the distant network.

The role social capital plays on individuals' employment prospects and wages has been studied in a number of settings. For instance, Bentolila *et al* (20010) argued that social capital may only help individuals in finding jobs in specific occupations rather than the ones in which they are more productive. Using data from the US and Europe, they found that although social contacts decrease unemployment duration by 1-3 months, they also reduce wages by at least 2.5%. The argument put forward by the authors is that higher status occupations are more difficult to find. Thus, individuals with social contacts are more willing to take up employment in a lower paid occupation which generates a mismatch in the labour market. Using the UK Quarterly Labour Force Survey, Kucel and Byrne (2008) estimated the effect of job search methods on over-education distinguishing between formal channels and social contacts. Their results reveal a lower probability of over-education when the job was found through formal channels (e.g., job advertisements), while personal contacts appear to increase the probability of over-education. However, Franzen and Hangartner (2006) get the opposite results. Using 2001 Swiss data they show that social networks and direct job application procedures lead to higher status occupations compared to formal channels.[6] Studies focusing on the effect of job search methods on graduates' over-education showed that finding a job through the universities' career office reduces the probability of over-education (see Blázquez and Mora, 2010; Carroll and Tani, 2014).

Regarding the role social capital plays on employment outcomes of immigrants, a number of studies have shown that having contacts with natives, who are more likely to have better information about the host country labour market and employment opportunities, has a stronger positive effect on immigrants' labour market outcomes compared to those with less/fewer contacts with natives (see Kanas et al, 2012; Hagan

[5] See Granovetter (1973), Granovetter (1983) and Montgomery (1991).

[6] Similar results were found by Horváth (2014) and Griesshaber and Seibel (2015), who found that personal networks and social participation leads to lower levels of over-education.

1998 and Putnam 2000; Drever and Hoffmeister 2008; Kazemipur 2006). However, immigrants who have better contacts with co-ethnic groups may also have a positive effect on their employment outcomes, especially if they are hindered by low proficiency in the host country's language. Using data on Latino immigrants residing in the US, Chavez *et al* (2008) showed that ethnic concentration (contacts with co-ethnics) may help immigrants in getting access to information about the host country as they are able to communicate in their native language, thus finding better paid jobs. However, their results show that the positive effect of ethnic concentration on immigrants' wages seemed to be effective only in the short run, as in the long run immigrants did not seem to benefit much from their co-ethnic contacts. On the other hand Kanas *et al* (2012), using German Socio-Economic Panel data to study social contacts of immigrants in Germany, found no evidence that ethnic concentration can improve immigrants' occupational status and wages. Finally, Piracha *et al* (2016), using data from Australia, found that social capital increases immigrants' entry into the labour market, especially for women and those employed in white-collar occupations, though they found no effect on wages.[7]

Notwithstanding the vast literature on social networks as well as labour market mismatch, none of the existing studies have analysed the effect of social capital on immigrants' and natives' over-education, especially using panel data analysis. Cross-sectional analyses do not allow one to examine the causal relationship between social capital and over-education while controlling for unobserved heterogeneity. For instance, individuals may have fewer contacts due to unobserved characteristics, or due to lack of employment over the years or a higher persistence of over-education, which is likely to limit their access to social networks (e.g., social interactions with co-workers). The contribution of this paper is therefore to analyse the extent to which social capital can, if at all, help immigrants and natives in finding a better matched job over time and hence attenuate the incidence of being over-educated.

## 3. Data and construction of variables

We use eleven waves (2001-2011) of the HILDA survey data to conduct the analysis. HILDA provides information about individuals' labour market activities, family formation, socio-economic status and their views and satisfaction with life and work.

[7] See also Catanzarite and Aguilera (2002) and Chiswick and Miller (2002, 2005).

Each wave includes approximately 17,000 individuals who live in Australia and are 15 years of age or older. One of the key advantages of HILDA is that it provides information on an annual basis and enables the use of panel data estimations which help to reduce heterogeneity bias arising from single cross-sectional data. One common problem with panel data is that individuals may drop out of the survey (e.g., emigration from Australia) as well as join the survey at a later wave (e.g., immigration to Australia) which leads to an unbalanced panel. In order to reduce the bias and skewness arising from such attrition, the HILDA provides longitudinal sample weights on a regular basis.[8]

In order to assess the importance of social capital on employment outcomes, the sample is restricted to the working age population (individuals aged between 15 and 64), who are in paid employment (excluding self-employed) and are not in full time education. Within the over-education literature, three main methods have been proposed to measure over-education: the job analysis method (JA), worker self-assessment (WA) and the realised matches method (RM). The job analysis method is seen as the objective measure that relies on documents and formal studies by countries and organisations, which is therefore often considered the preferred method to measure educational mismatch (Rumberger, 1987; Green et al, 2007; Hartog, 2000). For this study, the job analysis method is therefore used to estimate the dependent variable, the probability of being over-educated.

The HILDA survey covers a wide range of occupational categories based on a 2-digit scale taken from the Australian and New Zealand Standard Classification of Occupations (ANZSCO). Using these categories, each occupation is matched to the required level of education. There are 5 skill levels matched into a specific occupation category in the ANZSCO. The occupational breakdown available in the survey and their corresponding education level are shown in Table A1 in the Appendix.[9] In addition to the required level of education, having relevant work experience in the corresponding occupation may substitute formal education level. Since individuals are asked about the years of work experience they have obtained in their current occupation (tenure with the same occupation), besides the required level of education,

[8] For more details about the structure of HILDA see Summerfield et al. (2012).

[9] For more details, see ANZSCO, First Edition, Australian Bureau of Statistics, Canberra, Cat No. 1220.0.

those with relevant work experience have also been classified as being correctly matched. The 5 skill levels outlined in ANZSCO and the relevant work experience are shown in Table A2 in the Appendix. From the total sample, approximately 17 per cent of natives have been classified as over-educated, while a slightly higher proportion of immigrants (22 per cent) are over-educated. In addition, a relatively large proportion of both natives and immigrants are correctly-matched, as shown in Table 1.

Since our interest is in the probability of over/under-education of employed individuals, the sample has been the restricted to the labour force. Thus, the sample is restricted to 56,726 wage employees (45,543 natives and 11,183 immigrants).

The key interest for the analysis is the effect of different aspects that could be used as proxies for social capital. In order to assess the importance of social capital on individuals' educational mismatch, 8 variables have been chosen which represent individuals' social networks and contacts from a set of questions asked in the survey (summarised in Table A3). However, since these variables are likely to be highly correlated to each other, a social capital index has been constructed using the principal component analysis (PCA). The construction of the index, the explanation of the principal component used as well as the regression outcomes for the variables chosen are shown in section A4 in the Appendix. These variables cover individuals' satisfaction with life, their views about life as well as a number of activities. The following variables have been used:

*Amount of support:* The following questions were asked regarding the amount of support individuals get from other people.

- *'I often need help from other people but can't get it'*
- *'I have no one to lean on in times of trouble'*
- *'I often feel very lonely'*
- *'I seem to have a lot of friends'*.

The response ranges from 1 (strongly disagree) to 7 (strongly agree). Four dummy variables have been constructed that equal to one if the response was above average, and zero otherwise. This was mainly done since the PCA index is better estimated if all variables have the same scale of measurement (e.g. only dummy variables or only continuous variables).

*Frequency of contacts*: The following question was asked in HILDA:

- *'In general, about how often do you get together socially with friends or relatives not living with you?'*

The response ranges from 1 to 7 (every day, several times a week, about once a week, 2 or 3 times a month, about once a month, once or twice every 3 months). A dummy variable has been created equal to one if the individuals report to socially interact with friends and relatives at least twice a month, and zero if contact is less frequent than that. Another aspect used as a proxy for social capital is:

*Feeling part of the local community:*

This was asked among a set of questions related to their satisfaction in life. It is measured from 0 to 10, where 0 represents totally dissatisfied, 5 represents moderate and 10 represents totally satisfied. A dummy equal to one has been constructed if the response was above average, and zero otherwise.

*Social Participation:* The following questions were asked as part of this measure.

- *'Are you currently an active member of a sporting, hobby or community-based association?'*
- *'Do you belong to a trade union or employee association?'*

Both of these questions were already constructed as dummy variables as the response could only be answered with either a 'yes' or a 'no'.

Furthermore, another 'type' of index has been created that allows the construction of three different social capital indices. That is, instead of using all 8 variables into one single index using principal components, three indices have been constructed which allow to measure different aspects of social capital as a combination.[10] The three indices created are: 'reciprocity and trust', 'friends and support' and 'social participation'. The index 'reciprocity and trust' includes three dummy variables: help from others (dhelp), having someone to lean on (dsupport) and not feeling lonely (dtrust). This index adds one point if respondents receive help from others, one point for those who have someone to lean on and one for those who do not feel lonely, and

[10] A similar type of index was used by Aguilera et al (2003) to study the effect of social contacts on Mexican immigrants.

ranges from 0 to 3. Similarly, 'friends and support' ranges from 0 to 3 and adds one point if an individual states to have a lot of friends (dfriends), one additional point if they have frequent contacts (dfreq) and one point for feeling part of the local community (dcommunity). Finally, the 'social participation' index takes one point for those participating in clubs and associations (dclub) and one for union members (dunion) and ranges from 0 to 2.[11] Distinguishing among three indices allows us to analyse whether any particular one has a higher/lower impact on over-education.

Finally, an additional determinant, ethnic concentration, has been used to examine its effect on immigrants' incidence of being mismatched in the labour market. Since residing in a region with a high concentration of immigrants of the same ethnic group increases immigrants' chances of having contacts with co-ethnics such as neighbours or friends and relatives living nearby, ethnic concentration is considered to be one additional form of social capital. Ethnic concentration is defined as the population of a particular ethnic group residing in a specific area over the population of that region and can be written as:

$$Ethnic\_Concentration_{ijt} = \frac{Immigrant_{ijt}}{Immigrant_{jt}} * 100, \qquad (1)$$

where subscript $i$ represents a particular ethnic group residing in a specific region $j$ and $t$ represents the corresponding time period. In order to construct this variable, information on the residence population by country of birth and the Australian Capital Territory has been used from the Australian Bureau of Statistics 2006 and 2011, which provides census data on the population across Australia. This variable allows us to examine whether contacts with co-ethnics may have a significant effect on occupation-education mismatch.[12] The ethnic concentration variable is based on the share of immigrants of the same region who are employed. Since immigrants from the same country of origin tend to find employment in the same type of jobs, the ethnic concentration variable for the employed sample would allow us to capture any effect

[11] For instance, for the social participation index, if individuals respond to be both active members of clubs/associations and union members, the index takes the value of 2. If respondents report to be a member of only one of the two, the index takes the value of 1, and if individuals report to not being a member of any of the two, the index value is 0.
[12] The proportions of ethnic concentration for each ethnic group residing in a specific region have been merged into one single index.

due to increased competition for a particular type of job/firm in which immigrants from the same country of origin usually cluster.

Table 2 reports the descriptive statistics of the explanatory variables for the employed natives and immigrants. It is noticeable that both groups have an average of 9 and 10 years work experience, respectively, in their current occupation and 7 years tenure with the current employer. In addition, 38 per cent of both natives and immigrants have children below 15 years of age living in the household, while 8 per cent of the former and 7 per cent of the latter group report to suffer from health problems which may affect their work activities. Regarding the immigrant sample, 90 per cent report to be fluent in English and have spent an average of 24 years in Australia.[13]

As regards the countries of birth, 47 per cent originate from English-speaking countries[14], 16 per cent were born in Europe while 28 per cent originate from Asia. Immigrants are slightly more educated than natives with 39 per cent having completed at least a Bachelor's degree, while only 28 per cent of natives have the same level of education. For both groups, the majority lives in the Australian state of New South Wales followed by Victoria. As regards the dummy variables used for social capital, a relatively large percentage of both groups have reciprocity and trust (receive help from others, have someone to lean on in times of trouble and do not feel lonely). Regarding 'friends and support', a relatively large percentage of both groups report to have regular contacts with friends and relatives not living in the same household as well as feeling part of the local community. Approximately half of the population states to have a lot of friends. Looking at the social participation variables, 38 per cent of natives and 33 per cent of immigrants report to be active members of a sporting/hobby or community based club or association, while 29 per cent of natives and 27 per cent of immigrants report to be union members of employee associations. While in most cases immigrants are similar to natives, the latter group has a slightly higher percentage of social contacts than the former. In addition, the average proportion of ethnic concentration is 6 per cent.

[13] English proficiency includes those who state that English is the only language spoken at home or those who report to speak English very well. Approximately 67 per cent report to speak only English at home, while 23 per cent of those who do not speak only English report to know the language very well.
[14] English-speaking countries include New Zealand, United Kingdom, Ireland, Canada, USA and South Africa.

## 4. Empirical methodology

The main objective of this paper is to examine the effect of social capital on the incidence of over-education for immigrants and natives. When conducting a panel data analysis, it is of crucial importance to decide whether the estimation will be conducted using random effects or fixed effects. If time-variant control variables have little variation over time, the fixed effects estimator would lead to imprecise estimation coefficients (Cameron and Trivedi, 2009). Additionally, in the case of a limited dependent variable in short panels like in the HILDA survey (e.g. large cross-sectional units but few time periods), the fixed effects estimator can lead to problems with the degrees of freedom leading to inconsistent estimates of parameters (Maddala, 1987).

Besides modelling the extent to which social capital could contribute in the reduction of or accentuate the incidence of over-education, we also want to estimate the dynamics of over-education − the effect of over-education in *t-1* on the mismatch at time *t*. We therefore introduce a lagged dependent variable as an additional regressor in the model that directly captures the effect of past over-education status on current over-education. Given the above discussion, the best way to capture the effect of social capital on over-education is to employ a dynamic random effects probit model.

Although the main interest is to model the extent to which social capital could contribute to the reduction of or accentuate the incidence of over-education, excluding individuals who are under-educated could severely bias the estimated coefficients. We have therefore estimated the effects of the incidence of a mismatch by running separate regressions for the probability of over-education as well as the probability of under-education. This would allow us to analyse whether social contacts have any effect on individuals' being under-educated (in fact, the same worker could experience both types of mismatch over time).

The variable of interest is the incidence of a mismatch (e.g. the probability of being over-/under-educated) which is observed by a dummy latent dependent variable $y_{it}^{*}$ for any time period *t* such that

$$y_{it} = 1 \text{ if } y_{it}^{*} > 0 \tag{2}$$

$$y_{it} = 0 \text{ otherwise}$$

In order to model the dynamics of a mismatch, the latent dependent variable equation can be written in the following form:

$$y_{it}^{*} = \gamma y_{it-1} + \beta x_{it}' + \alpha_i + \varepsilon_{it}, \quad (i = 1, \ldots, N;\ t = 2, \ldots, T) \quad (3)$$

where the model is estimated for the time period t ≥ 2. $y_{it}^{*}$ denotes the latent variable for each individual $i$ at time $t$, $y_{it-1}$ represents the lagged dependent variable, $x_{it}'$ includes a set of explanatory variables, $\alpha_i$ is the time invariant unobserved individual-specific random effects and $\varepsilon_{it}$ is the error term, where the individual specific component of the error term $\varepsilon_{it}$ is uncorrelated with the independent explanatory variables $x_{it}$ such that $\varepsilon_{it} \sim N(0, \sigma_u^2)$, and the composite error term is $v_{it} = \alpha_i + \varepsilon_{it}$. However, the random effects model makes the assumption that the explanatory variables $x_{it}'$ are uncorrelated with $\alpha_i$. If this assumption is violated, it will lead to biased and inconsistent parameters. A common solution to this unrealistic assumption is to use the Mundlak (1978) and Chamberlain (1984) approach which proposes a solution to control for any unobserved fixed component of each time variant variable in the estimation. Therefore, $\alpha_i$ and $x_{it}'$ are specified parametrically and can be incorporated directly in the random effects model such that:

$$\alpha_i = \bar{X}_i a + u_i, \quad (4)$$

where $\bar{X}_i$ is a vector capturing the time averaged mean values for every time-varying covariates and assumes $u_i \sim N(0, \sigma_u^2)$ where $u_i$ is the residual time-invariant unobserved heterogeneity which is independent of $x_{it}'$ and $\varepsilon_{it}$. Thus, the random effects specification can be used which gives equivalent fixed-effects estimates as the means of the time-varying variables are included in the model which capture any unobserved time-invariant effects of the explanatory variables. Furthermore, one concern regarding the social capital variable could be the non-random distribution of social capital amongst those finding a job through it (for instance, endogeneity linked to unobserved non-cognitive skills such as social or introvert behaviour). For instance, social capital could be a result of different personality traits (e.g. social/introvert behaviour) among those looking for a job through social networks. Similarly, for the immigrant sample, ethnic concentration is likely to be endogenous if individuals self-select themselves to reside in specific regions (e.g. selecting to reside in regions with a high ethnic concentration of their own ethnic group). Thus, if social interactions are a result of different social behaviours or self-selection into specific regions of individuals seeking employment, the estimates of the relevant variables that capture social networks are likely to be over/under estimated. However, since this social/introvert personality, as well as the choice to reside in specific areas, are likely to be unobserved fixed components of an individual, the Mundlak corrections are likely to capture those unobservables (if present), since the corrections are used for exactly that purpose.

Another problem in the dynamic random effects specification arises with the inclusion of the lagged dependent variable in the equation. This might be spurious due to endogeneity of the initial conditions problem, since the standard random effects model assumes the initial condition of the dependent variable to be exogenous (Heckman, 1981). However, if the initial condition is correlated with $\alpha_i$, the standard random effects probit model would be inconsistent as it would overestimate state dependence (Heckman, 1981). Thus, $y_{it-1}$ would be correlated with the composite error term $v_{it}$. Three main methods have been developed to account for the initial condition problem (Heckman, 1981; Orme, 2001 and Wooldridge, 2005). Since all three estimators have been proven to give similar (if not identical) results, we choose the Wooldridge (2005) estimator to conduct the analysis.

Wooldridge (2005) proposed a Conditional Maximum Likelihood (CML) estimator where the distribution is conditional on the initial value of the dependent variable $y_{i1}$ and a set of exogenous regressors such that

$$c_i | y_{i\,initial}, z_i \sim \text{Normal}(\alpha_0 + \alpha_{1initial} + z_i\alpha_2, \sigma_\alpha^2), \tag{5}$$

where

$$c_i = \alpha_0 + \alpha_1 y_{iinitial} + z_i\alpha_2 + \alpha_i. \tag{6}$$

Thus, the model can be specified as follows,

$$y_{it}^* = \gamma y_{it-1} + x_{it}'\beta + \delta y_{i1} + \zeta \bar{X}_i + v_{it}, \qquad (\, i = 1, \ldots, N;\ t = 2, \ldots, T) \tag{7}$$

where $v_{it} = \eta_i + \varepsilon_i$, $y_{i1}$ is the initial value of the dependent variable, $\bar{X}_i$ are the mean values for all time-variant variables that capture any unobserved time-invariant characteristics of the time-variant covariates and the rest are as explained above.

Furthermore, since educational mismatch is only observed for the employed individuals, a potential selection bias may occur if the individuals are non-randomly selected from the population. However, in the HILDA survey, only 4 per cent of the sample is unemployed. Since the percentage of unemployed individuals is relatively low, a selection issue would typically not be a major concern. However, in order to control for possible selection into employment, the level of education has been included as an additional regressor in the over-education equation.

Although a random effects model with Mundlak corrections controls for omitted variables which may be correlated with the explanatory variables, it does not control for potential endogeneity of social capital. That is, social networks may be a result of shocks which could affect the level of social capital and therefore educational mismatch. For instance, the level of social contacts may depend on the accessibility to and availability of resources and networks in their region of residence (or working area). In order to control for potential endogeneity of social capital and ethnic concentration, interaction variables between year of survey and the region of residence have been included in all regressions. This allows us to control for potential shocks which may affect the level of social capital.

Another potential identification issue when studying the effect of social networks on labour market outcomes is the possible reverse causality. That is, while higher social contacts and the interaction with friends and relatives may help individuals to find a job that matches their level of education, it could be argued that a higher-status job could provide individuals with more resources and enable them to increase their social networks (e.g. meeting more people in their work environment, socialise with co-workers etc). In fact, in the case of immigrants, it may give them more opportunities to form social networks with natives, which could positively affect their employment outcome.

There are two ways to control for reverse causality: we could either use an instrumental variable model or use lagged variables. Finding an appropriate instrument in these kinds of models, and especially in our data, is almost impossible. We therefore follow Kanas *et al* (2012) and control for potential reverse causality by including lagged variables of social contacts, which is a more appropriate method in a random effects model. One concern when including the lagged variables is the possibility of serial correlation, which may invalidate the results. However, Baltagi (2001) and Wooldridge (2002) argue that serial correlation is not an issue when there are relatively large number of observations (N) and a small time-period (T), which is the case in our data. They explain that in such cases clustering standard errors is sufficient to provide consistent estimates.

## 5. Results and discussion

Table 3 presents the results obtained from the dynamic random effects probit model (Wooldridge, 2005) with Mundlak corrections controlling for the initial conditions problem and unobserved heterogeneity. Columns 1 and 2 present the incidence of over/under educated of the total sample, while columns 3-4 and 5-6 report separate results for natives and immigrants respectively.

Since the effect of social networks on labour market outcomes are expected to vary according to ethnicity (e.g. native or immigrants) as well as according to gender, the main analysis has been conducted separately for natives/immigrants and for males/females. Table 4 presents the results obtained for the male sample with separate estimates for natives and immigrants, while Table 5 reports the results of the incidence of over/under education for the female sample.

Tables 6, 7 and 8 report the results obtained using the alternative measure of social capital, namely 'social participation', 'reciprocity and trust' and 'friends and support' for males and females separately. Tables 9a-b and 10a-b report the results obtained when distinguishing between those who have completed at least a Bachelor's degree and those whose education is below that level. Since different skill levels are likely to be affected differently in the labour market, social capital may have different effects on over-education for the higher skilled and the lower skilled group.[15]

[15] In fact, individuals are likely to self-select themselves into specific types of networks according to their education level as well as according to gender and ethnicity (Rosenbaum et al., 1999; Smith, 2000).

### *5.1 Dynamics of over-education*

Before discussing the role of social capital in determining the incidence of over-education, we first discuss the dynamics of over-education for both natives and immigrants, with a particular focus on state dependence. As Mavromaras *et al* (2012) pointed out, there is a difference between simple persistence and state dependence. While simple persistence refers to the duration of an individual being over-educated, state dependence is associated with the causal effect of the lagged dependent variable of over-education at *t-1* on over-education at period *t*. The nature of the HILDA data allows us to control for actual state dependence which arises when the state of being over-educated in the previous period has a causal effect on the state of being over-educated in some future period.

In all models, a highly statistically significant effect of over-education in period *t-1* on current over-education is observed, confirming the existence of state dependence in the Australian labour market. As expected, the coefficient of the lagged dependent variable is larger for immigrants compared to the native sample as shown in Table 4. The exogeneity of the initial conditions in the dynamic random effects model is rejected by the highly statistically significant coefficient of the initial state of over-education. This gives support to the use of Wooldridge (2005) estimator. In addition, the average mean values for time variant variables are also included to capture any correlation of the individual-specific component of the error term with the explanatory variables.

Once unobserved heterogeneity and initial conditions have been accounted for, the results show that those who had been over-educated in the previous period are 10 per cent more likely to be over-educated in the future (see Table 3).[16] Furthermore, the results show that immigrants experience a higher degree of state dependence compared to natives. That is, 14 per cent of immigrants' over-education at time *t* can be explained by the previous state of over-education, while only 9 per cent of natives who have experienced over-education in the previous period are still over-educated at time *t*. However, while 2 per cent of native's under-education can be explained by the

[16] The existence of state dependence in over-education has been supported by a number of studies (see Mavromaras *et al,* 2012 for Australia; Cuesta and Budria, 2012 for Germany and Joona *et al*, 2012 for Sweden).

previous state of under-education, the results show that the undereducated immigrants do not experience any state dependence.

### *5.2 Social capital and over-education*

#### *5.2.1 The PCA index*

When using the PCA index, the marginal effects for the total sample show that social capital leads to an increased probability of being over-educated for the native population, thus generating a mismatch in the Australian labour market (see Table 3).

Columns 1 and 2 of Table 4 report the results obtained for the total male population, while columns 3-6 report the incidence of over/under education of natives and immigrants respectively. The immigrant sample includes years since the date of arrival in Australia, its square, English language proficiency as well as ethnic networks (percentage of immigrants living in a region with a high ethnic concentration). It is clear that while social capital (PCA index) results in a higher incidence of over-education for native females, no significant effect is observed for the immigrant sample. Since social capital may have a different impact on over-education for different ethnic groups, separate regression estimates have been conducted distinguishing between different groups of migrants.[17] However, ethnic concentration appears to have a significant and positive effect on female immigrants' over-education. In particular, for each percentage point increase in ethnic concentration, the incidence of over-education increases by 2 percentage points, indicating that interactions with co-ethnics are likely to worsen immigrants' labour market outcomes in terms of finding a matched job over time. However, no effect is observed for males. These results suggest that females, compared to males, tend to rely more on their social contacts and in particular contacts with co-ethnics in order to find employment. Perhaps females look for more flexible employment opportunities (e.g., because of childcare constraints) and use contacts with other similar females to get similar kind of jobs. This is especially so if females are tied migrants, i.e., they followed their husbands to the host country, in which case they might be willing to take up part-time jobs as it could be that they prefer to spend more time at home with

[17] The results of the robustness checks for different groups of migrants are not reported but are available upon request.

their children. Therefore, they are likely to meet more co-ethnics, for instance by participating in organisations dedicated to their own ethnic group, who could perhaps help them in finding any part-time or casual job which does not necessarily match their education level.

One explanation for the insignificant effect of the PCA index on the immigrant sample could be that it captures mainly social interactions with individuals in the host country regardless of ethnicity and region of residence. As outlined by previous studies, immigrants are likely to create more contacts with co-ethnics rather than with natives as they tend to trust their co-ethnics more than the natives (Glaeser *et al.*, 2000; Buchan *et al.*, 2002). It could also be that immigrants (especially recent arrivals) may not have had the chance yet to form networks with the natives and may therefore only rely on social contacts with co-ethnics who are more easily accessible upon arrival (e.g., self-selecting themselves into areas with a high percentage of co-ethnics, or participating in social activities dedicated specifically to their own ethnic group). However, no significant effect was found when analysing the results by years spent in Australia, indicating that time spent has no impact on network formation as the PCA index remains insignificant.[18] In addition, social contacts do not seem to have any effect on the under-education group for both, natives and immigrants.

### *5.2.2 Alternative index*

Although the PCA index reduces collinerarity and provides a relatively stable proxy for social capital, one drawback is that it does not capture the effect of different 'types' of social capital as outlined in the literature. It is possible that a particular type of social capital may have a stronger or weaker effect on educational mismatch than others, which are not captured if it is measured as one single index. Thus, in order to analyse the sensitivity of the measurement of social capital on labour market outcomes, the models have been re-estimated by constructing an alternative measure, which consists of three indices: 'social participation', 'reciprocity and trust' and 'friends and support'.

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[18] As a robustness check, we have furthermore run separate estimates with social network by systematically adding personal and family characteristics, job characteristics and health status in order to investigate potential collinearity. Since the social capital index remains unchanged, we can conclude that collinearity is not an issue. To conserve space the results from these estimates are not presented in this paper but are available upon request.

The results indicate that social participation (defined as active participation in clubs, associations or trade unions) and friends and support have a statistically significant effect on the incidence of over-education for natives when considering the total sample as shown in Table 6.

In particular, social capital acquired through active participation in clubs, associations and union membership worsens educational mismatch for native males, while friends and support accentuates over-education for native females (see Tables 7 and 8). In addition, social participation appears to worsen educational mismatch for female immigrants, while no effect is observed for the male sample.

Although previous studies have found that socialising with friends may play an important role in finding employment, the results suggest that they are not very effective in finding a correctly matched job. Reciprocity and trust does not seem to affect over-education for any group.

Regarding other human capital indicators, as expected, those with at least a Bachelor's degree are more likely to be over-educated compared to those with lower levels of education. Knowledge of the host country's language does not show to have any effect on immigrants' incidence of over-education.[19] However, years spent since migration does reduce the incidence of over-education, with a stronger effect on female immigrants. These results are in line with previous research, which found that years spent in the host country improves immigrants' economic assimilation in the host country.[20] In addition, tenure with the current occupation reduces the incidence of over-education for all groups, with a relatively higher impact on immigrants. Perhaps networks could be more effective in reducing educational mismatch once immigrants have acquired the relevant experience in that particular occupation.

### *5.3 Effect of social capital by education level*

Tables 9 and 10 report results by levels of education. Tables 9a (using PCA) and 9b (using Alternative Index) report results for male natives and immigrants who have

[19] A possible explanation for the insignificant effect of host country language skills might be that 90 per cent of the immigrant group have been classified as fluent English speakers.
[20] See Chiswick and Miller, 2009

completed at least a Bachelor's degree, while Tables 10a and 10b report the results obtained for those with a lower level of education (e.g. diploma or less).

While the PCA index including all social capital variables becomes insignificant for both the higher educated natives and immigrants, interesting results are obtained when distinguishing between social participation, friends and support and reciprocity and trust. The results indicate that friends and support decrease the incidence of over-education for male immigrants. In particular, the incidence of over-education for higher educated male immigrants decreases by about 3 per cent with friends and support. Higher educated are likely to have formed better 'quality' contacts in the host country by creating networks with similarly higher educated individuals. Thus, more years in education may provide graduates with a wider network, especially with other graduates who are likely to be more informed about (better) job opportunities.

For the case of natives, however, while friends and support remains insignificant, social participation decreases the incidence of over-education for higher educated females, indicating the importance of 'weak' ties for female natives with a Bachelor's degree or higher (Granovetter, 1973; Granovetter, 1983; Montgomery 1991). This in turn could provide them with information about the labour market and effectively link them with employers outside their own network. However, the magnitude of this correction is approximately half compared to that for male immigrants. A possible explanation could be that if migrants moved to the host country for employment reasons, they might put more effort in finding a better matched job in the host country.

Higher educated female immigrants on the other hand do not seem to benefit much from their social capital, while ethnic concentration remains significant and positively correlated with the incidence of over-education even for the higher educated group. Although the significance has reduced, the magnitude has increased compared to the total sample (including all levels of education). In other words, higher educated females experience higher levels of over-education which is generated by their contacts with co-ethnics, increasing the incidence of educational mismatch by nearly 6 per cent. Regarding the lower educated group shown in Tables 10a and 10b, social participation and friends and support are both statistically significant and positively affect the incidence of over-education for the native sample for males and females respectively, while no effect is observed for immigrants. The lower educated are likely to rely more on their social contacts in order to find employment leading to a mismatch in the labour market. Perhaps the lower educated group might have limited access to ('better') networks than those with a university degree. Furthermore, if lower educated are not looking to follow a specific occupation pathway then they are likely to end up in 'lower status' jobs which may not necessarily match their education level.

## 6. Conclusions

The aim of this paper was to analyse the extent to which social and ethnic capital can reduce the problem of over-education for natives and immigrants in the Australian labour market. Previous studies have mainly focused on the importance of social capital on labour market outcomes in terms of employment entry and wages, but not much on the types of jobs individuals enter. Particularly, they do not take into consideration whether the jobs individuals find through social capital matches ones education qualification. Using longitudinal data from HILDA, this paper examined to what extent social capital contributed to reduce or enhance the incidence of educational mismatch in the Australian labour market taking into consideration the causal effect of social capital. After controlling for unobserved heterogeneity and addressing potential endogeneity of social networks, the findings suggest that social capital exacerbates the incidence of over-education, particularly for females. In particular, social capital worsens the incidence of over-education for natives, while ethnic capital (defined as ethnic concentration) is the main contributor in increasing the probability of over-education for immigrants. These results are in line with a number of studies which argue that contacts with co-ethnics might help immigrants in finding employment and in some cases increased wages, but are less effective in providing them with higher-status jobs (Wiley, 1967; Catanzarite and Aguilera, 2002). Males' co-ethnic networks on the other hand do not seem to have any impact on over-education.

Finally, higher educated male immigrants are likely to benefit more from their contacts compared to the lower educated group. The results suggest that male immigrants with higher education are likely to put more effort in finding a matched job, especially since many of them come to Australia with a job offer. In addition, years spent in education may have contributed in creating ‘better quality’ networks with other individuals who might be employed in higher status jobs, enabling them to access necessary resources leading to improved labour market conditions.

**Conflict of Interest:**

The authors declare that they have no conflict of interest.

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**Table 1 Percentage of educational mismatch (Natives and Immigrants)**

| | Natives | Immigrants | Total |
|---|---|---|---|
| Over-educated | 16.76 | 21.73 | 17.74 |
| Under-educated | 13.08 | 9.39 | 12.35 |
| Correctly matched | 70.16 | 68.88 | 69.90 |
| Total | 100 | 100 | 100 |

Source: Authors' calculation using HILDA survey.

**Table 2 Descriptive Statistics for employed individuals**

| | Native-born Australians | | Foreign-born | |
|---|---|---|---|---|
| Variables | Mean | s.d. | Mean | s.d. |
| Age | 38.52 | 11.97 | 42.81 | 11.00 |
| Married or cohabiting | 0.65 | 0.48 | 0.72 | 0.45 |
| Presence of children aged 14 years or less | 0.38 | 0.49 | 0.38 | 0.49 |
| English Proficiency | | | 0.9 | 0.30 |
| Years since migration | | | 24.09 | 13.68 |
| Lives in major city | 0.62 | 0.49 | 0.80 | 0.40 |
| Inner | 0.25 | 0.44 | 0.13 | 0.33 |
| Outer | 0.11 | 0.31 | 0.06 | 0.23 |
| Remote | 0.02 | 0.14 | 0.01 | 0.11 |
| ABS unemployment rate in major statistical region | 5.13 | 1.19 | 4.96 | 1.13 |
| Unemployment proportion in last financial year | 2.14 | 10.62 | 2.08 | 10.48 |
| Tenure with current occupation | 09.23 | 09.51 | 10.12 | 10.07 |
| Tenure with current employer | 6.98 | 7.89 | 6.61 | 7.12 |
| Has more than one job | 0.09 | 0.28 | 0.08 | 0.27 |
| Bachelor's degree or higher | 0.28 | 0.45 | 0.39 | 0.49 |
| Diploma | 0.11 | 0.32 | 0.13 | 0.33 |
| Certificate Level 4 | 0.16 | 0.37 | 0.14 | 0.34 |
| Certificate Level 2/3 | 0.09 | 0.28 | 0.05 | 0.22 |
| Certificate Level 1 or compulsory secondary education | 0.32 | 0.47 | 0.26 | 0.44 |
| Less than compulsory secondary education | 0.04 | 0.19 | 0.03 | 0.17 |
| Long-term health that condition that limits or prevents the type or amount of work | 0.08 | 0.27 | 0.07 | 0.26 |
| Europe | | | 0.16 | 0.36 |
| Asia | | | 0.28 | 0.45 |
| ESC | | | 0.47 | 0.50 |
| Other countries | | | 0.09 | 0.29 |
| New South Wales | 0.28 | 0.45 | 0.33 | 0.47 |
| Victoria | 0.25 | 0.43 | 0.24 | 0.42 |
| Queensland | 0.22 | 0.42 | 0.17 | 0.37 |
| South Australia | 0.09 | 0.29 | 0.07 | 0.25 |
| Western Australia | 0.09 | 0.28 | 0.13 | 0.34 |
| Tasmania | 0.03 | 0.18 | 0.01 | 0.11 |
| Northern Territory | 0.01 | 0.09 | 0.02 | 0.12 |
| Australian Capital Territory | 0.02 | 0.15 | 0.04 | 0.18 |

| | | | | |
|---|---|---|---|---|
| **Social Capital dummies** | | | | |
| Reciprocity and Trust | | | | |
| dhelp | 0.82 | 0.38 | 0.82 | 0.38 |
| dsupport | 0.83 | 0.37 | 0.80 | 0.40 |
| dtrust | 0.73 | 0.44 | 0.70 | 0.46 |
| Friends and Support | | | | |
| dfriends | 0.53 | 0.50 | 0.49 | 0.50 |
| dfreq | 0.79 | 0.41 | 0.74 | 0.44 |
| dcommunity | 0.73 | 0.44 | 0.73 | 0.46 |
| Social Participation | | | | |
| dclub | 0.38 | 0.49 | 0.33 | 0.47 |
| dunion | 0.29 | 0.46 | 0.27 | 0.45 |
| **Ethnic concentration (%)** | | | 5.51<br>4.23 | |
| **Observations** | **45,543** | | **11,183** | |

Source: Authors' calculations using HILDA survey.

**Table 3 Dynamic Random Effects Probit model Natives vs. Immigrants- PCA Index (Marginal Effects)**

| Dynamic Random Effects Probit Model | | | | | | |
|---|---|---|---|---|---|---|
| | All | | Natives | | Immigrants | |
| | Over-educated | Under-educated | Over-educated | Under-educated | Over-educated | Under-educated |
| $y_{t-1}$ | 0.100*** | 0.0182*** | 0.0905*** | 0.0216*** | 0.137*** | 0.00571 |
| | (0.0106) | (0.0064) | (0.0111) | (0.0079) | (0.0295) | (0.0063) |
| $y_{initial}$ | 0.489*** | 0.155*** | 0.466*** | 0.165*** | 0.550*** | 0.0928** |
| | (0.0220) | (0.0211) | (0.0246) | (0.0234) | (0.0488) | (0.0400) |
| Immigrant | 0.00862** | -0.00380** | | | | |
| | (0.0041) | (0.0019) | | | | |
| Female | 0.00245 | 0.000273 | -0.00105 | 0.000352 | 0.0237** | -0.000163 |
| | (0.0029) | (0.0015) | (0.0030) | (0.0019) | (0.0095) | (0.0015) |
| Married or cohabiting | -0.00591 | 0.00073 | -0.00457 | 0.00148 | -0.0139 | -0.00165 |
| | (0.0044) | (0.0020) | (0.0043) | (0.0025) | (0.0156) | (0.0026) |
| Presence of children (<15 years) | 0.000791 | -0.000943 | 0.000188 | -0.000799 | 0.00421 | -0.000828 |
| | (0.0033) | (0.0019) | (0.0033) | (0.0023) | (0.0112) | (0.0018) |
| YSM | | | | | -0.00262** | -0.000243 |
| | | | | | (0.0012) | (0.0003) |
| YSM squared/100 | | | | | 2.38E-05 | 7.32E-06 |
| | | | | | (0.0000) | (0.0000) |
| English Proficiency | | | | | -0.0179 | 0.00222 |
| | | | | | (0.0146) | (0.0021) |
| Education level: Bachelor's degree or higher | 0.0371*** | | 0.0312*** | | 0.0561*** | |
| | (0.0048) | | (0.0051) | | (0.0121) | |
| Proportion of unemployment in last financial year | 0.000562*** | 0.00018*** | 0.000583*** | 0.000194** | 0.000443 | 7.95E-05 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0003) | (0.0001) |
| Tenure with current occupation | -0.00091*** | -0.00595*** | -0.00073*** | -0.00683*** | -0.00190*** | -0.00239 |
| | (0.0002) | (0.0011) | (0.0002) | (0.0012) | (0.0006) | (0.0016) |
| Tenure with current employer | -0.000852*** | -0.000204 | -0.000752*** | -0.000341 | -0.00131 | 9.61E-05 |
| | (0.0003) | (0.0002) | (0.0003) | (0.0003) | (0.0010) | (0.0002) |
| Has more than one job | 0.0116** | -0.000136 | 0.0100** | 7.12E-05 | 0.0206 | -0.000305 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0050) | (0.0021) | (0.0049) | (0.0026) | (0.0180) | (0.0020) |
| Long-term health condition | 0.0160*** | -0.00318 | 0.0162*** | -0.00400* | 0.0109 | -0.000287 |
| | (0.0053) | (0.0019) | (0.0056) | (0.0024) | (0.0144) | (0.0023) |
| Social Capital Index (PCA) t-1 | 0.00138 | -0.000246 | 0.00184* | -0.000637 | -0.00153 | 0.000526 |
| | (0.0010) | (0.0005) | (0.0010) | (0.0007) | (0.0029) | (0.0006) |
| Ethnic Concentration (%) t-1 | | | | | 0.0130** | -0.00225 |
| | | | | | (0.0062) | (0.0019) |
| Interaction year*Queensland | -0.00015 | 0.000511 | -0.000802 | 0.000245 | 0.00470* | 0.000914 |
| | (0.0008) | (0.0005) | (0.0008) | (0.0006) | (0.0028) | (0.0009) |
| Interaction year*South Australia | 0.000594 | 0.00051 | 0.000589 | 0.000359 | -0.000767 | 0.000332 |
| | (0.0012) | (0.0007) | (0.0011) | (0.0008) | (0.0042) | (0.0008) |
| Interaction year*Western Australia | -0.00211* | 0.000584 | -0.00162 | 0.000829 | -0.00375 | 0.000256 |
| | (0.0012) | (0.0007) | (0.0013) | (0.0008) | (0.0037) | (0.0006) |
| Interaction year*Tasmania | -0.00172 | 0.000363 | -0.00135 | 0.000146 | -0.00596 | 0.000726 |
| | (0.0022) | (0.0011) | (0.0022) | (0.0014) | (0.0074) | (0.0015) |
| Interaction year*Northern Territory | -0.00708* | -0.00167 | -0.00655 | -0.00215 | -0.00917 | -0.000292 |
| | (0.0038) | (0.0019) | (0.0042) | (0.0027) | (0.0075) | (0.0012) |
| Interaction year*Australian Capital Territory | -0.00308 | -0.00083 | -0.00336 | -0.000715 | 3.47E-06 | -0.00113 |
| | (0.0021) | (0.0010) | (0.0023) | (0.0012) | (0.0044) | (0.0012) |
| Log likelihood | -11051.165 | -8361.081 | -8743.126 | -7024.8631 | -2265.2114 | -1296.5591 |
| Observations | 41,830 | 28,490 | 33,490 | 23,482 | 8,340 | 5,008 |
| Number of id | 9,142 | 6,569 | 7,251 | 5,368 | 1,891 | 1,201 |

*Notes:* All models include year dummies, region of residence, age and its square, controls for living in a city, inner or remote area, the unemployment rate in major statistical region and Mundlak corrections. The social capital index (PCA) includes 8 dummies: active participation in clubs and associations, member of a trade union, frequent contacts with friends, having a lot of friends, receiving help from others, feeling part of the local community, does not feel lonely and does have someone to lean on in times of trouble.

**Table 4 Dynamic Random Effects Probit model Natives vs. Immigrants- PCA Index (Marginal Effects) Males**

| | All | | Natives | | Immigrants | |
|---|---|---|---|---|---|---|
| | Over-educated | Under-educated | Over-educated | Under-educated | Over-educated | Under-educated |
| $y_{t-1}$ | 0.0889*** | 0.0203* | 0.0754*** | 0.0236* | 0.148*** | 0.00508 |
| | (0.0142) | (0.0114) | (0.0139) | (0.0135) | (0.0492) | (0.0072) |
| $y_{initial}$ | 0.495*** | 0.138*** | 0.490*** | 0.160*** | 0.494*** | 0.0382 |
| | (0.0311) | (0.0261) | (0.0344) | (0.0302) | (0.0737) | (0.0273) |
| Immigrant | 0.00174 | -0.00148 | | | | |
| | (0.0049) | (0.0026) | | | | |
| Married or cohabiting | -5.94E-05 | 0.00468 | -0.000715 | 0.00529 | 0.00527 | 0.000796 |
| | (0.0053) | (0.0030) | (0.0053) | (0.0038) | (0.0153) | (0.0019) |
| Presence of children (<15 years) | -0.00452 | -0.000595 | -0.00395 | -8.64E-05 | -0.0101 | -0.000783 |
| | (0.0041) | (0.0026) | (0.0041) | (0.0031) | (0.0127) | (0.0024) |
| YSM | | | | | 0.000228 | -0.000352 |
| | | | | | (0.0015) | (0.0004) |
| YSM squared/100 | | | | | -1.20E-05 | 1.05E-05 |
| | | | | | (0.0000) | (0.0000) |
| English Proficiency | | | | | -0.0382* | 0.00224 |
| | | | | | (0.0226) | (0.0026) |
| Education level: Bachelor's degree or higher | 0.0331*** | | 0.0312*** | | 0.0373*** | |
| | (0.0067) | | (0.0076) | | (0.0133) | |
| Proportion of 0 unemployment in last financial year | 0.000494*** | 0.000199* | 0.000574*** | 0.000211* | 0.000303 | 6.00E-05 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0004) | (0.0001) |
| Tenure with current occupation | -0.00105*** | -0.00520*** | -0.000825*** | -0.00592*** | -0.00219*** | -0.00179 |
| | (0.0003) | (0.0016) | (0.0003) | (0.0017) | (0.0008) | (0.0015) |
| Tenure with current employer | -0.00118*** | -0.000148 | -0.00121*** | -0.000279 | -0.00104 | 0.00013 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) | (0.0013) | (0.0003) |
| Has more than one job | 0.00769 | -0.000463 | 0.00521 | -0.000279 | 0.0194 | -0.000728 |
| | (0.0072) | (0.0030) | (0.0071) | (0.0038) | (0.0235) | (0.0021) |
| Long-term health condition | 0.0106 | -0.00361 | 0.0101 | -0.00691* | 0.00546 | 0.0113 |
| | (0.0068) | (0.0028) | (0.0070) | (0.0038) | (0.0177) | (0.0145) |
| Social Capital Index (PCA) t-1 | 0.000745 | -0.000618 | 0.00173 | -0.000823 | -0.00374 | 0.000186 |
| | (0.0013) | (0.0007) | (0.0014) | (0.0009) | (0.0036) | (0.0005) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Ethnic Concentration (%) t-1 | | | | | 0.00797 | -0.00237 |
| | | | | | (0.0072) | (0.0022) |
| Interaction year*Queensland | -0.000118 | 0.000557 | -0.00096 | 0.000281 | 0.00646* | 0.000852 |
| | (0.0011) | (0.0006) | (0.0011) | (0.0007) | (0.0035) | (0.0010) |
| Interaction year*South Australia | 0.00146 | 8.36E-05 | 0.00135 | 3.25E-05 | 0.0025 | -0.000222 |
| | (0.0015) | (0.0009) | (0.0014) | (0.0011) | (0.0055) | (0.0008) |
| Interaction year*Western Australia | -0.000341 | 0.000203 | 6.85E-05 | 0.000711 | -5.12E-06 | -0.000293 |
| | (0.0016) | (0.0008) | (0.0016) | (0.0011) | (0.0044) | (0.0007) |
| Interaction year*Tasmania | 0.000292 | -0.000467 | -0.00044 | -0.00132 | 0.0134 | 0.00215 |
| | (0.0033) | (0.0017) | (0.0031) | (0.0020) | (0.0159) | (0.0023) |
| Interaction year*Northern Territory | -0.00618 | -0.00428 | -0.00572 | -0.00467 | -0.0283** | -0.0023 |
| | (0.0071) | (0.0033) | (0.0069) | (0.0039) | (0.0144) | (0.0024) |
| Interaction year*Australian Capital Territory | -0.00354 | -0.00234 | -0.00481 | -0.00324 | 0.00404 | -0.000155 |
| | (0.0026) | (0.0015) | (0.0030) | (0.0021) | (0.0046) | (0.0008) |
| Log likelihood | -5393.1832 | -4205.2462 | -4268.852 | -3526.5581 | -1090.9154 | -637.04256 |
| Observations | 20,969 | 14,809 | 16,682 | 12,206 | 4,287 | 2603 |
| Number of id | 4,509 | 3,350 | 3,543 | 2,732 | 966 | 618 |

*Notes:* All models include year dummies, region of residence, age and its square, controls for living in a city, inner or remote area, the unemployment rate in major statistical region and Mundlak corrections. The social capital index (PCA) includes 8 dummies: active participation in clubs and associations, member of a trade union, frequent contacts with friends, having a lot of friends, receiving help from others, feeling part of the local community, does not feel lonely and does have someone to lean on in times of trouble. The ethnic concentration variable has been capture using 13 ethnic groups residing in the 8 states of Australia. YSM stands for years since migration.

**Table 5 Dynamic Random Effects Probit model Natives vs. Immigrants- PCA Index (Marginal Effects) Females**

| | Dynamic Random Effects Probit model | | | | | |
|---|---|---|---|---|---|---|
| | All | | Natives | | Immigrants | |
| | Over-educated | Under-educated | Over-educated | Under-educated | Over-educated | Under-educated |
| $y_{t-1}$ | 0.110*** | 0.0154** | 0.103*** | 0.0190** | 0.129*** | 0.000428 |
| | (0.0158) | (0.0066) | (0.0172) | (0.0081) | (0.0375) | (0.0012) |
| $y_{initial}$ | 0.470*** | 0.176*** | 0.429*** | 0.167*** | 0.597*** | 0.196 |
| | (0.0309) | (0.0349) | (0.0345) | (0.0361) | (0.0656) | (0.1220) |
| Immigrant | 0.0170** | -0.00582** | | | | |
| | (0.0068) | (0.0027) | | | | |
| Married or cohabiting | -0.00975 | -0.00419 | -0.0059 | -0.00366 | -0.0392 | -0.00111 |
| | (0.0068) | (0.0034) | (0.0064) | (0.0041) | (0.0306) | (0.0020) |
| Presence of children (<15 years) | 0.00781 | -0.00263 | 0.00576 | -0.00305 | 0.0192 | -0.0004 |
| | (0.0054) | (0.0026) | (0.0052) | (0.0034) | (0.0193) | (0.0008) |
| YSM | | | | | -0.00614*** | -1.50E-05 |
| | | | | | (0.0021) | (0.0001) |
| YSM squared/100 | | | | | 7.17e-05** | 5.05E-07 |
| | | | | | (0.0000) | (0.0000) |
| English Proficiency | | | | | -0.00095 | 0.00049 |
| | | | | | (0.0196) | (0.0008) |
| Education level: Bachelor's degree or higher | 0.0410*** | | 0.0313*** | | 0.0763*** | |
| | (0.0069) | | (0.0068) | | (0.0210) | |
| Proportion of unemployment in last financial year | 0.000602*** | 0.000155** | 0.000575*** | 0.000180* | 0.000611 | 1.82E-05 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0004) | (0.0000) |
| Tenure with current occupation | -0.000710** | -0.00680*** | -0.000594** | -0.00790*** | -0.00116 | -0.00068 |
| | (0.0003) | (0.0015) | (0.0003) | (0.0016) | (0.0010) | (0.0010) |
| Tenure with current employer | -0.000263 | -0.000258 | 6.83E-06 | -0.000381 | -0.00226 | -1.96E-05 |
| | (0.0005) | (0.0003) | (0.0005) | (0.0003) | (0.0015) | (0.0001) |
| Has more than one job | 0.0145** | 8.69E-05 | 0.0134** | 0.000572 | 0.0175 | -0.000293 |
| | (0.0067) | (0.0028) | (0.0064) | (0.0037) | (0.0258) | (0.0006) |
| Long-term health condition | 0.0210*** | -0.00306 | 0.0210** | -0.000606 | 0.0173 | -0.000867 |
| | (0.0079) | (0.0026) | (0.0083) | (0.0038) | (0.0223) | (0.0014) |
| Social Capital Index (PCA) t-1 | 0.00192 | 0.000175 | 0.00187* | -0.000325 | 0.00181 | 0.000246 |
| | (0.0015) | (0.0008) | (0.0015) | (0.0010) | (0.0047) | (0.0004) |
| Ethnic Concentration (%) t-1 | | | | | 0.0219** | -0.000441 |
| | | | | | (0.0107) | (0.0008) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Interaction year*Queensland | -0.000296 | 0.000369 | -0.000654 | 7.67E-05 | 0.000489 | 0.000229 |
| | (0.0012) | (0.0007) | (0.0012) | (0.0008) | (0.0044) | (0.0004) |
| Interaction year*South Australia | -0.000317 | 0.000947 | -0.000102 | 0.000695 | -0.00316 | 0.000226 |
| | (0.0017) | (0.0010) | (0.0017) | (0.0013) | (0.0062) | (0.0004) |
| Interaction year*Western Australia | -0.00420** | 0.00107 | -0.00350* | 0.000997 | -0.0086 | 0.000179 |
| | (0.0019) | (0.0010) | (0.0020) | (0.0014) | (0.0060) | (0.0003) |
| Interaction year*Tasmania | -0.00378 | 0.00112 | -0.00237 | 0.0016 | -0.0215*** | 0.000123 |
| | (0.0030) | (0.0015) | (0.0029) | (0.0018) | (0.0073) | (0.0004) |
| Interaction year*Northern Territory | -0.00937** | 0.000564 | -0.00822 | 0.0011 | -0.0138 | 0.000217 |
| | (0.0046) | (0.0029) | (0.0055) | (0.0050) | (0.0101) | (0.0005) |
| Interaction year*Australian Capital Territory | -0.00158 | 0.00026 | -0.00114 | 0.00104 | -0.00441 | -0.000886 |
| | (0.0033) | (0.0014) | (0.0034) | (0.0017) | (0.0080) | (0.0014) |
| Log likelihood | -5608.7547 | -4114.0905 | -4432.0033 | -3458.5767 | -1143.4858 | -624.1779 |
| Observations | 20,861 | 13,681 | 16,808 | 11,276 | 4,053 | 2,405 |
| Number of id | 4,633 | 3,219 | 3,708 | 2,636 | 925 | 583 |

*Notes:* All models include year dummies, region of residence, age and its square, controls for living in a city, inner or remote area, the unemployment rate in major statistical region and Mundlak corrections. The social capital index 'social participation' includes active participation of clubs and associations and member of a trade union, the index 'friends and support' includes frequent contacts with friends, having a lot of friends and receiving help from others and the index 'reciprocity and trust' includes feeling part of the local community, does not feel lonely and does have someone to lean on in times of trouble.

**Table 6 Dynamic Random Effects Probit model Natives vs. Immigrants – Alternative Index (Marginal Effects)**

| | Dynamic Random Effects Probit model | | | | | |
|---|---|---|---|---|---|---|
| | All | | Natives | | Immigrants | |
| | Over-educated | Under-educated | Over-educated | Under-educated | Over-educated | Under-educated |
| $y_{t-1}$ | 0.101*** | 0.0186*** | 0.0916*** | 0.0220*** | 0.137*** | 0.00574 |
| | (0.0107) | (0.0065) | (0.0112) | (0.0080) | (0.0297) | (0.0064) |
| $y_{initial}$ | 0.487*** | 0.156*** | 0.463*** | 0.165*** | 0.557*** | 0.0935** |
| | (0.0220) | (0.0208) | (0.0245) | (0.0231) | (0.0490) | (0.0400) |
| Immigrant | 0.00833** | -0.00390** | | | | |
| | (0.0041) | (0.0019) | | | | |
| Female | 0.000639 | -0.00171 | -0.0022 | -0.00215 | 0.0184** | -0.000631 |
| | (0.0029) | (0.0016) | (0.0030) | (0.0020) | (0.0092) | (0.0015) |
| Married or cohabiting | -0.00544 | 0.000794 | -0.00413 | 0.00156 | -0.0132 | -0.00149 |
| | (0.0043) | (0.0020) | (0.0043) | (0.0025) | (0.0152) | (0.0025) |
| Presence of children (<15 years) | 0.000895 | -0.000791 | 0.000225 | -0.000587 | 0.0046 | -0.000785 |
| | (0.0033) | (0.0018) | (0.0033) | (0.0023) | (0.0110) | (0.0018) |
| YSM | | | | | -0.00251** | -0.000216 |
| | | | | | (0.0012) | (0.0002) |
| YSM squared/100 | | | | | 2.27E-05 | 6.86E-06 |
| | | | | | (0.0000) | (0.0000) |
| English Proficiency | | | | | -0.0137 | 0.00239 |
| | | | | | (0.0138) | (0.0022) |
| Education level: Bachelor's degree or higher | 0.0383*** | | 0.0321*** | | 0.0571*** | |
| | (0.0049) | | (0.0052) | | (0.0119) | |
| Proportion of unemployment in last financial year | 0.000560*** | 0.000172*** | 0.000584*** | 0.000189** | 0.000417 | 7.51E-05 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0003) | (0.0001) |
| Tenure with current occupation | -0.000946*** | -0.00594*** | -0.000753*** | -0.00683*** | -0.00198*** | -0.00237 |
| | (0.0002) | (0.0011) | (0.0002) | (0.0012) | (0.0006) | (0.0015) |
| Tenure with current employer | -0.000920*** | -0.000212 | -0.000801*** | -0.000346 | -0.00146 | 8.84E-05 |
| | (0.0003) | (0.0002) | (0.0003) | (0.0003) | (0.0010) | (0.0002) |
| Has more than one job | 0.0111** | -0.000406 | 0.00963** | -0.000302 | 0.0182 | -0.000293 |
| | (0.0049) | (0.0020) | (0.0049) | (0.0026) | (0.0173) | (0.0020) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Long-term health condition | 0.0162*** | -0.00302 | 0.0163*** | -0.00386 | 0.0107 | -0.000193 |
| | (0.0054) | (0.0019) | (0.0057) | (0.0024) | (0.0142) | (0.0023) |
| SCI: Social Participation t-1 | 0.00577*** | -0.000715 | 0.00470** | -0.00113 | 0.0123* | 0.000393 |
| | (0.0020) | (0.0011) | (0.0020) | (0.0014) | (0.0065) | (0.0011) |
| SCI: Friends and Support t-1 | 0.00217 | 0.000636 | 0.00307** | 0.000919 | -0.0042 | -0.000162 |
| | (0.0014) | (0.0007) | (0.0014) | (0.0010) | (0.0041) | (0.0006) |
| SCI: Reciprocity and Trust t-1 | -9.71E-05 | -0.000689 | 0.00017 | -0.00138 | -0.00127 | 0.000827 |
| | (0.0013) | (0.0007) | (0.0014) | (0.0009) | (0.0038) | (0.0009) |
| Ethnic Concentration (%) t-1 | | | | | 0.0132** | -0.00214 |
| | | | | | (0.0061) | (0.0018) |
| Interaction year*Queensland | -0.000175 | 0.000521 | -0.000819 | 0.000266 | 0.00453* | 0.000907 |
| | -0.000813 | -0.000459 | -0.000813 | -0.000555 | -0.00274 | -0.000855 |
| Interaction year*South Australia | 0.000564 | 0.000512 | 0.000543 | 0.000367 | -0.000551 | 0.000335 |
| | -0.00115 | -0.000676 | -0.00113 | -0.000836 | -0.00415 | -0.000743 |
| Interaction year*Western Australia | -0.00210* | 0.000621 | -0.00166 | 0.000877 | -0.00346 | 0.000251 |
| | -0.00122 | -0.000648 | -0.00126 | -0.000831 | -0.00358 | -0.000636 |
| Interaction year*Tasmania | -0.00179 | 0.000381 | -0.00142 | 0.000189 | -0.00596 | 0.000653 |
| | -0.00224 | -0.00111 | -0.00215 | -0.00135 | -0.00721 | -0.00146 |
| Interaction year*Northern Territory | -0.00705* | -0.00156 | -0.00652 | -0.00204 | -0.00906 | -0.000201 |
| | -0.0038 | -0.00189 | -0.00422 | -0.00268 | -0.00758 | -0.00117 |
| Interaction year*Australian Capital Territory | -0.00308 | -0.000896 | -0.00341 | -0.000798 | 0.000194 | -0.00112 |
| | -0.00206 | -0.000969 | -0.0023 | -0.0012 | -0.00428 | -0.00113 |
| Log likelihood | -11039.399 | -8336.4491 | -8736.5811 | -7001.901 | -2257.6862 | -1293.6255 |
| Observations | 41,830 | 28,490 | 33,490 | 23,482 | 8,340 | 5,008 |
| Number of id | 9,142 | 6,569 | 7,251 | 5,368 | 1,891 | 1,201 |

*Notes:* All models include year dummies, region of residence, age and its square, controls for living in a city, inner or remote area, the unemployment rate in major statistical region and Mundlak corrections. The social capital index 'social participation' includes active participation of clubs and associations and member of a trade union, the index 'friends and support includes frequent contacts with friends, having a lot of friends and receiving help from others and the index 'reciprocity and trust' includes feeling part of the local community, does not feel lonely and does have someone to lean on in times of trouble. The ethnic concentration variable has been captured using 13 ethnic groups residing in the 8 states of Australia. YSM stands for years since migration.

**Table 7 Dynamic Random Effects Probit model Natives vs. Immigrants – Alternative Index (Marginal Effects) Males**

| Dynamic Random Effects Probit model | | | | | | |
|---|---|---|---|---|---|---|
| | All | | Natives | | Immigrants | |
| | Over-educated | Under-educated | Over-educated | Under-educated | Over-educated | Under-educated |
| $y_{t-1}$ | 0.0894*** | 0.0203* | 0.0761*** | 0.0237* | 0.146*** | 0.00432 |
| | (0.0142) | (0.0112) | (0.0140) | (0.0131) | (0.0483) | (0.0064) |
| $y_{initial}$ | 0.495*** | 0.136*** | 0.491*** | 0.158*** | 0.499*** | 0.0373 |
| | (0.0311) | (0.0256) | (0.0344) | (0.0294) | (0.0737) | (0.0275) |
| Immigrant | 0.00187 | -0.00195 | | | | |
| | (0.0049) | (0.0025) | | | | |
| Married or cohabiting | 0.000148 | 0.00482 | -0.000278 | 0.00557 | 0.00484 | 0.000733 |
| | (0.0052) | (0.0030) | (0.0053) | (0.0037) | (0.0150) | (0.0017) |
| Presence of children (<15 years) | -0.00435 | -0.000621 | -0.00376 | -6.32E-05 | -0.011 | -0.000801 |
| | (0.0041) | (0.0026) | (0.0041) | (0.0031) | (0.0125) | (0.0021) |
| YSM | | | | | 0.000298 | -0.000293 |
| | | | | | (0.0014) | (0.0003) |
| YSM squared/100 | | | | | -1.28E-05 | 9.22E-06 |
| | | | | | (0.0000) | (0.0000) |
| English Proficiency | | | | | -0.0351 | 0.00202 |
| | | | | | (0.0220) | (0.0025) |
| Education level: Bachelor's degree or higher | 0.0330*** | | 0.0307*** | | 0.0380*** | |
| | (0.0066) | | (0.0076) | | (0.0132) | |
| Proportion of unemployment in last financial year | 0.000498*** | 0.000197** | 0.000576*** | 0.000212* | 0.000278 | 5.37E-05 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0004) | (0.0001) |
| Tenure with current occupation | -0.00107*** | -0.00518*** | -0.000841*** | -0.00589*** | -0.00223*** | -0.00164 |
| | (0.0003) | (0.0015) | (0.0003) | (0.0017) | (0.0008) | (0.0015) |
| Tenure with current employer | -0.00123*** | -0.000138 | -0.00127*** | -0.000263 | -0.00103 | 0.000119 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0003) | (0.0012) | (0.0002) |
| Has more than one job | 0.00723 | -0.000625 | 0.00495 | -0.000611 | 0.018 | -0.000515 |
| | (0.0071) | (0.0029) | (0.0070) | (0.0037) | (0.0227) | (0.0020) |
| Long-term health condition | 0.0107 | -0.00344 | 0.00998 | -0.00672* | 0.00525 | 0.0106 |
| | (0.0068) | (0.0028) | (0.0070) | (0.0036) | (0.0176) | (0.0140) |
| SCI: Social Participation t-1 | 0.00654** | -0.00174 | 0.00721** | -0.00218 | 0.00325 | -0.000229 |
| | (0.0028) | (0.0016) | (0.0029) | (0.0020) | (0.0080) | (0.0012) |

| | | | | | | |
|---|---|---|---|---|---|---|
| SCI: Friends and Support t-1 | | | | | | |
| | 0.00053 | 0.000597 | 0.00239 | 0.00158 | -0.00877* | -0.000967 |
| | (0.0019) | (0.0010) | (0.0019) | (0.0014) | (0.0052) | (0.0011) |
| SCI: Reciprocity and Trust t-1 | -5.65E-05 | -0.00108 | 0.00013 | -0.00186 | -0.000521 | 0.00084 |
| | (0.0018) | (0.0009) | (0.0018) | (0.0012) | (0.0047) | (0.0011) |
| Ethnic Concentration (%) t-1 | | | | | 0.00797 | -0.00216 |
| | | | | | (0.0072) | (0.0021) |
| Interaction year*Queensland | -0.00013 | 0.000545 | -0.00095 | 0.000258 | 0.00647* | 0.000816 |
| | -0.00108 | -0.000618 | -0.00109 | -0.000723 | -0.00343 | -0.000981 |
| Interaction year*South Australia | 0.00147 | 7.39E-05 | 0.00132 | 2.58E-05 | 0.00238 | -0.00014 |
| | -0.00147 | -0.00088 | -0.00143 | -0.00108 | -0.00541 | -0.000723 |
| Interaction year*Western Australia | -0.000311 | 0.000244 | 7.04E-05 | 0.000758 | 0.000301 | -0.000222 |
| | -0.00156 | -0.00081 | -0.0016 | -0.00105 | -0.00432 | -0.000618 |
| Interaction year*Tasmania | 0.000273 | -0.000443 | -0.000502 | -0.00129 | 0.0132 | 0.00194 |
| | -0.00324 | -0.00165 | -0.00307 | -0.00203 | -0.0153 | -0.00211 |
| Interaction year*Northern Territory | -0.00609 | -0.00413 | -0.0056 | -0.00442 | -0.0278** | -0.00211 |
| | -0.00704 | -0.00316 | -0.00686 | -0.00381 | -0.014 | -0.00227 |
| Interaction year*Australian Capital Territory | -0.00352 | -0.00241 | -0.00485* | -0.00329 | 0.00388 | -0.000137 |
| | -0.00256 | -0.00151 | -0.00295 | -0.00205 | -0.00452 | -0.000716 |
| Log likelihood | -5390.2741 | -4192.1274 | -4264.724 | -3512.5017 | -1088.4682 | -634.41303 |
| Observations | 20,969 | 14,809 | 16,682 | 12,206 | 4,287 | 2,603 |
| Number of id | 4,509 | 3,350 | 3,543 | 2,732 | 966 | 618 |

*Notes:* All models include year dummies, region of residence, age and its square, controls for living in a city, inner or remote area, the unemployment rate in major statistical region and Mundlak corrections. The social capital index 'social participation' includes active participation of clubs and associations and member of a trade union, the index 'friends and support includes frequent contacts with friends, having a lot of friends and receiving help from others and the index 'reciprocity and trust' includes feeling part of the local community, does not feel lonely and does have someone to lean on in times of trouble. The ethnic concentration variable has been captured using 13 ethnic groups residing in the 8 states of Australia. YSM stands for years since migration.

**Table 8 Dynamic Random Effects Probit model Natives vs. Immigrants – Alternative Index (Marginal Effects) Females**

| | Dynamic Random Effects Probit model | | | | | |
|---|---|---|---|---|---|---|
| | All | | Natives | | Immigrants | |
| | Over-educated | Under-educated | Over-educated | Under-educated | Over-educated | Under-educated |
| $y_{t-1}$ | 0.112*** | 0.0160** | 0.104*** | 0.0196** | 0.129*** | 0.000395 |
| | (0.0160) | (0.0068) | (0.0174) | (0.0083) | (0.0382) | (0.0011) |
| $y_{initial}$ | 0.467*** | 0.178*** | 0.426*** | 0.169*** | 0.608*** | 0.203* |
| | (0.0307) | (0.0346) | (0.0343) | (0.0359) | (0.0656) | (0.1240) |
| Immigrant | 0.0166** | -0.00566** | | | | |
| | (0.0067) | (0.0026) | | | | |
| Married or cohabiting | -0.00928 | -0.00423 | -0.00571 | -0.00384 | -0.0352 | -0.000919 |
| | (0.0068) | (0.0034) | (0.0064) | (0.0041) | (0.0295) | (0.0018) |
| Presence of children (<15 years) | 0.00809 | -0.00234 | 0.00599 | -0.00271 | 0.0202 | -0.000346 |
| | (0.0054) | (0.0026) | (0.0052) | (0.0033) | (0.0192) | (0.0007) |
| YSM | | | | | -0.00589*** | -8.64E-06 |
| | | | | | (0.0020) | (0.0001) |
| YSM squared/100 | | | | | 6.79e-05** | 3.92E-07 |
| | | | | | (0.0000) | (0.0000) |
| English Proficiency | | | | | 0.00394 | 0.000475 |
| | | | | | (0.0183) | (0.0008) |
| Education level: Bachelor's degree or higher | 0.0440*** | | 0.0340*** | | 0.0772*** | |
| | (0.0071) | | (0.0071) | | (0.0207) | |
| Proportion of unemployment in last financial year | 0.000595*** | 0.000148* | 0.000571*** | 0.000172* | 0.000588 | 1.60E-05 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0004) | (0.0000) |
| Tenure with current occupation | -0.000761** | -0.00681*** | -0.000629** | -0.00791*** | -0.00129 | -0.000617 |
| | (0.0003) | (0.0014) | (0.0003) | (0.0016) | (0.0010) | (0.0009) |
| Tenure with current employer | -0.000347 | -0.000294 | -2.95E-05 | -0.000418 | -0.00269* | -2.37E-05 |
| | (0.0005) | (0.0003) | (0.0005) | (0.0004) | (0.0015) | (0.0001) |
| Has more than one job | 0.0139** | -0.00022 | 0.0130** | 0.00024 | 0.0158 | -0.000299 |
| | (0.0067) | (0.0028) | (0.0064) | (0.0036) | (0.0252) | (0.0006) |
| Long-term health condition | 0.0213*** | -0.00293 | 0.0211** | -0.000447 | 0.0173 | -0.000774 |
| | (0.0080) | (0.0026) | (0.0083) | (0.0038) | (0.0224) | (0.0013) |
| SCI: Social Participation t-1 | 0.00351 | 0.00016 | 0.00107 | -0.000124 | 0.0220** | 0.000272 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0029) | (0.0016) | (0.0028) | (0.0020) | (0.0105) | (0.0005) |
| SCI: Friends and Support t-1 | 0.00386* | 0.00057 | 0.00375* | 7.38E-05 | 0.00144 | 0.000275 |
| | (0.0020) | (0.0010) | (0.0020) | (0.0013) | (0.0067) | (0.0005) |
| SCI: Reciprocity and Trust t-1 | -0.000237 | -0.00011 | 0.000188 | -0.000517 | -0.00142 | 0.00014 |
| | (0.0019) | (0.0010) | (0.0019) | (0.0013) | (0.0063) | (0.0003) |
| Ethnic Concentration (%) t-1 | | | | | 0.0205** | -0.000394 |
| | | | | | (0.0103) | (0.0007) |
| Interaction year*Queensland | -0.000312 | 0.000397 | -0.000652 | 0.000138 | 0.000197 | 0.000192 |
| | (0.0012) | (0.0007) | (0.0012) | (0.0008) | (0.0044) | (0.0003) |
| Interaction year*South Australia | -0.000372 | 0.000948 | -0.000129 | 0.000688 | -0.00284 | 0.000206 |
| | (0.0017) | (0.0010) | (0.0017) | (0.0013) | (0.0061) | (0.0004) |
| Interaction year*Western Australia | -0.00417** | 0.0011 | -0.00355* | 0.00106 | -0.00809 | 0.00015 |
| | (0.0019) | (0.0010) | (0.0020) | (0.0014) | (0.0059) | (0.0003) |
| Interaction year*Tasmania | -0.00379 | 0.00112 | -0.00233 | 0.00161 | -0.0218*** | 0.000109 |
| | (0.0030) | (0.0015) | (0.0029) | (0.0018) | (0.0076) | (0.0003) |
| Interaction year*Northern Territory | -0.00934** | 0.00067 | -0.00824 | 0.00115 | -0.0142 | 0.000215 |
| | (0.0047) | (0.0028) | (0.0055) | (0.0049) | (0.0104) | (0.0005) |
| Interaction year*Australian Capital Territory | -0.0017 | 0.000229 | -0.00127 | 0.00101 | -0.00399 | -0.00078 |
| | (0.0033) | (0.0014) | (0.0034) | (0.0017) | (0.0076) | (0.0012) |
| Log likelihood | -5599.0012 | -4102.1636 | -4426.3559 | -3449.348 | -1138.2312 | -620.6281 |
| Observations | 20,861 | 13,681 | 16,808 | 11,276 | 4,053 | 2,405 |
| Number of id | 4,633 | 3,219 | 3,708 | 2,636 | 925 | 583 |

*Notes:* All models include year dummies, region of residence, age and its square, controls for living in a city, inner or remote area, the unemployment rate in major statistical region and Mundlak corrections. The social capital index 'social participation' includes active participation of clubs and associations and member of a trade union, the index 'friends and support includes frequent contacts with friends, having a lot of friends and receiving help from others and the index 'reciprocity and trust' includes feeling part of the local community, does not feel lonely and does have someone to lean on in times of trouble. The ethnic concentration variable has been captured using 13 ethnic groups residing in the 8 states of Australia. YSM stands for years since migration.

## Table 9 Dynamic Random Effects Probit model – Bachelor's Degree or higher (Marginal Effects)

### Table 9a

Social Capital Index (PCA) Having a Bachelor's degree or higher

| | Natives | | Immigrants | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| $y_{t-1}$ | 0.102*** | 0.104*** | 0.233*** | 0.248*** |
| | (0.0253) | (0.0239) | (0.0707) | (0.0513) |
| $y_{initial}$ | 0.356*** | 0.333*** | 0.399*** | 0.351*** |
| | (0.0463) | (0.0483) | (0.0991) | (0.0752) |
| **Social Capital Index (PCA) t-1** | 0.00109 | -0.0025 | -0.0114 | 0.0202 |
| | (0.00576) | (0.00432) | (0.0101) | (0.0138) |
| **Ethnic Concentration (%) t-1** | | | -0.00631 | 0.0609* |
| | | | (0.0222) | (0.0321) |
| Observations | 4,471 | 5,520 | 1,682 | 1,645 |
| Number of id | 851 | 1,130 | 353 | 358 |

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

### Table 9b

Social Capital - Alternative Index Having a Bachelor's degree or higher

| | Natives | | Immigrants | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| $y_{t-1}$ | 0.103*** | 0.104*** | 0.231*** | 0.254*** |
| | (0.0253) | (0.0239) | (0.0688) | (0.0525) |
| $y_{initial}$ | 0.357*** | 0.312*** | 0.406*** | 0.353*** |
| | (0.0466) | (0.0468) | (0.0991) | (0.0756) |
| **Social Participation t-1** | 0.00791 | -0.0137* | -0.0048 | 0.0502* |
| | (0.0098) | (0.00703) | (0.02) | (0.029) |
| **Friends and Support t-1** | -0.00365 | 0.00236 | -0.0279* | 0.0107 |
| | (0.00809) | (0.00568) | (0.0144) | (0.0203) |
| Reciprocity and Trust t-1 | 0.00129 | -0.00362 | 0.000235 | 0.0129 |
| | (0.00782) | (0.0058) | (0.0124) | (0.0196) |
| **Ethnic Concentration (%) t-1** | | | -0.00743 | 0.0592* |
| | | | (0.0214) | (0.0323) |
| Observations | 4,471 | 5,520 | 1,682 | 1,645 |
| Number of id | 851 | 1,130 | 353 | 358 |

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

*Notes:* Both Tables include year dummies, Mundlak corrections and the same control variables as used for the total sample.

## Table 10 Dynamic Random Effects Probit model – Less than a Bachelor's degree (Marginal Effects)

### Table 10a

Social Capital Index (PCA) Education less than a Bachelor's degree

| VARIABLES | Natives | | Immigrants | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| $y_{t-1}$ | 0.0463*** | 0.0834*** | 0.0659 | 0.0153 |
| | (0.0137) | (0.0223) | (0.057) | (0.0164) |
| $y_{initial}$ | 0.601*** | 0.512*** | 0.563*** | 0.825*** |
| | (0.0464) | (0.0498) | (0.114) | (0.0829) |
| **Social Capital Index (PCA) t-1** | 0.00119 | 0.00215* | 0.000403 | -0.00131 |
| | (0.00086) | (0.00115) | (0.0019) | (0.00142) |
| **Ethnic Concentration (%) t-1** | | | 0.00783 | -0.00097 |
| | | | (0.00648) | (0.0024) |
| Observations | 12,211 | 11,288 | 2,605 | 2,408 |
| Number of id | 2,734 | 2,639 | 619 | 583 |

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

### Table 10b

Social Capital - Alternative Index Education less than a Bachelor's degree

| VARIABLES | Natives | | Immigrants | |
|---|---|---|---|---|
| | Males | Females | Males | Females |
| $y_{t-1}$ | 0.0474*** | 0.0852*** | 0.0625 | 0.0153 |
| | (0.0139) | (0.0226) | (0.0545) | (0.0165) |
| $y_{initial}$ | 0.602*** | 0.513*** | 0.574*** | 0.836*** |
| | (0.0462) | (0.0495) | (0.115) | (0.0802) |
| **Social Participation t-1** | 0.00412** | 0.00477** | 0.0146 | 0.0034 |
| | (0.00207) | (0.00239) | (0.00544) | (0.00274) |
| **Friends and Support t-1** | 0.00216* | 0.00330** | -0.00525 | -0.00324 |
| | (0.00129) | (0.00166) | (0.00142) | (0.00063) |
| Reciprocity and Trust t-1 | 0.000141 | 0.000603 | -0.00269 | -0.0017 |
| | (0.00116) | (0.00146) | (0.00089) | (0.00175) |
| **Ethnic Concentration (%) t-1** | | | -0.00254 | -0.00176 |
| | | | (0.00793) | (0.00107) |
| Observations | 12,211 | 11,288 | 2,605 | 2,408 |
| Number of id | 2,734 | 2,639 | 619 | 583 |

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

*Notes:* Both Tables include year dummies, Mundlak corrections and the same control variables as used for the total sample.

## Appendix

### Table A1 ANZSCO – Occupational breakdown – 2digit level and their corresponding skill requirements

| | | Skill Level(s) |
|---|---|---|
| **1** | **MANAGERS** | |
| 11 | Chief Executives, General Managers and Legislators | 1 |
| 12 | Farmers and Farm Managers | 1 |
| 13 | Specialist Managers | 1 |
| 14 | Hospitality, Retail and Service Managers | 2 |
| **2** | **PROFESSIONALS** | |
| 21 | Arts and Media Professionals | 1 |
| 22 | Business, Human Resource and Marketing Professionals | 1 |
| 23 | Design, Engineering, Science and Transport Professionals | 1 |
| 24 | Education Professionals | 1 |
| 25 | Health Professionals | 1 |
| 26 | ICT Professionals | 1 |
| 27 | Legal, Social and Welfare Professionals | 1 |
| **3** | **TECHNICIANS AND TRADES WORKERS** | |
| 31 | Engineering, ICT and Science Technicians | 2 |
| 32 | Automotive and Engineering Trades Workers | 3 |
| 33 | Construction Trades Workers | 3 |
| 34 | Electrotechnology and Telecommunications Trades Workers | 3 |
| 35 | Food Trades Workers | 2,3 |
| 36 | Skilled Animal and Horticultural Workers | 3 |
| 39 | Other Technicians and Trades Workers | 3 |
| **4** | | |
| 41 | Health and Welfare Support Workers | 2 |
| 42 | Carers and Aides | 4 |
| 43 | Hospitality Workers | 4,5 |
| 44 | Protective Service Workers | 2,3,4,5 |
| 45 | Sports and Personal Service Workers | 3,4 |
| **5** | **CLERICAL AND ADMINISTRATIVE WORKERS** | |
| 51 | Office Managers and Program Administrators | 2 |
| 52 | Personal Assistants and Secretaries | 3 |
| 53 | General Clerical Workers | 4 |
| 54 | Inquiry Clerks and Receptionists | 4 |
| 55 | Numerical Clerks | 4 |
| 56 | Clerical and Office Support Workers | 5 |
| 59 | Other Clerical and Administrative Workers | 3,4 |
| **6** | **SALES WORKERS** | |
| 61 | Sales Representatives and Agents | 3,4 |
| 62 | Sales Assistants and Salespersons | 5 |

| | | |
|---|---|---|
| 63 | Sales Support Workers | 5 |
| **7** | **MACHINERY OPERATORS AND DRIVERS** | |
| 71 | Machine and Stationary Plant Operators | 4 |
| 72 | Mobile Plant Operators | 4 |
| 73 | Road and Rail Drivers | 4 |
| 74 | Store persons | 4 |
| **8** | **LABOURERS** | |
| 81 | Cleaners and Laundry Workers | 5 |
| 82 | Construction and Mining Labourers | 4,5 |
| 83 | Factory Process Workers | 4,5 |
| 84 | Farm, Forestry and Garden Workers | 5 |
| 85 | Food Preparation Assistants | 5 |
| 89 | Other Labourers | 5 |

Source: ANZSCO, Australian Bureau of Statistics, cat. no. 1220

**Table A2 ANZSCO Definition of skill levels – Required formal education and years of relevant experience**

| Skill Level | |
|---|---|
| 1 | Bachelor degree or higher qualification (At least five years of relevant experience required to substitute for formal qualification) |
| 2 | NZ Register Diploma or AQF Associate Degree, Advanced Diploma or Diploma (At least three years of relevant experience required to substitute formal qualification) |
| 3 | NZ Register Level 4 qualification or AQF Certificate IV or AQF Certificate III including at least two years of on-the-job training (At least three years of relevant experience required to substitute for formal qualification) |
| 4 | NZ Register Level 2/3 qualification or AQF Certificate II or III (At least one year of relevant experience required to substitute formal qualification) |
| 5 | NZ Register Level 1 qualification or AQF Certificate I/compulsory secondary education |

Source: ANZSCO, Australian Bureau of Statistics, cat. no. 1220.

## Table A3 Social capital variables and definitions

| Literature or explanation of variable | Question asked in survey (HILDA Self Completion Questionnaire) | |
|---|---|---|
| **Reciprocity and trust** | I often need help from other people but can't get it' | Strongly disagree=1, Strongly agree=7 |
| | I have no one to lean on in times of trouble' | Strongly disagree=1, Strongly agree=7 |
| | I often feel very lonely' | Strongly disagree=1, Strongly agree=7 |
| **Friends and support** | I seem to have a lot of friends' | Strongly disagree=1, Strongly agree=7 |
| | How often get together socially with friends/relatives not living with you?' | Every day=1, Several times a week=2, About onc week=3, 2 or 3 times a month=4, About once a month=5, Once or twice every 3 months=6, Less than once every 3 months=7 |
| | Feeling part of your local community' | Totally dissatisfied=0, Neither satisfied nor dissatisfied=5, totally satisfied=10 |
| **Social participation** | Currently an active member of a sporting/hobby/community based club or association' | Yes=1, No=0 |
| | Union membership of employee association' | Yes=1, No=0 |

## A4 Construction of the Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) is a statistical method which aims to reduce multicollinearity by using an orthogonal transformation to transform a set of explanatory variables into a set of principal components, which are uncorrelated one another. By that, it reduces the dimensionality of the data keeping as much of the variation as possible. Thus, the first principal component of the set of variables chosen has the largest variation available in the data. The following tables report the results obtained using 8 variables related to social capital in order to construct the PCA index.

**Table A4 Pearson Correlation Coefficients between the social capital variables**

| | Correlation coefficients between social capital variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | dhelp | dsupport | dtrust | dfriends | dfreq | dcommunity | dclub | dunion |
| dhelp | 1 | | | | | | | |
| dsupport | 0.3405 | 1 | | | | | | |
| dtrust | 0.3153 | 0.3589 | 1 | | | | | |
| dfriends | 0.1707 | 0.1989 | 0.211 | 1 | | | | |
| dfreq | 0.1134 | 0.1521 | 0.1126 | 0.2136 | 1 | | | |
| dcommunity | 0.1311 | 0.1343 | 0.1616 | 0.1647 | 0.0887 | 1 | | |
| dclub | 0.0712 | 0.0729 | 0.0716 | 0.1215 | 0.1113 | 0.1517 | 1 | |
| dunion | 0.0406 | 0.0286 | 0.0419 | 0.0312 | -0.0136 | 0.058 | 0.0444 | 1 |

**Table A5 Eigenvalues and Cumulative Proportion**

| Component | Eigenvalue | Cumulative Proportion |
|---|---|---|
| Comp1 | 2.05525 | 0.2569 |
| Comp2 | 1.09168 | 0.3934 |
| Comp3 | 1.02514 | 0.5215 |
| Comp4 | 0.907117 | 0.6349 |
| Comp5 | 0.842497 | 0.7402 |
| Comp6 | 0.764481 | 0.8358 |
| Comp7 | 0.68223 | 0.921 |
| Comp8 | 0.631605 | 1.00 |

**Table A6 Outcomes of the Principal Components (eigenvectors)**

| | Principal Components (eigenvectors) at time $t$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables ($t$) | $PC_{1t}$ | $PC_{2t}$ | $PC_{3t}$ | $PC_{4t}$ | $PC_{5t}$ | $PC_{6t}$ | $PC_{7t}$ | $PC_{8t}$ |
| dhelp ($x_{1t}$) | 0.4376 | -0.3351 | 0.0854 | -0.0822 | 0.1955 | 0.1273 | 0.7586 | 0.2284 |
| dsupport ($x_{2t}$) | 0.4679 | -0.3229 | 0.0049 | -0.0179 | 0.1507 | 0.0889 | -0.2376 | -0.7677 |
| dtrust ($x_{3t}$) | 0.4618 | -0.2989 | 0.0837 | -0.0966 | 0.0113 | -0.1017 | -0.5786 | 0.5795 |
| dfriends ($x_{4t}$) | 0.3843 | 0.2325 | -0.2012 | 0.2817 | -0.3243 | -0.7361 | 0.1626 | -0.0707 |
| dfreq ($x_{5t}$) | 0.2885 | 0.3035 | -0.4759 | 0.536 | 0.04 | 0.5397 | -0.058 | 0.1209 |
| dcommunity ($x_{6t}$) | 0.3043 | 0.3663 | 0.1951 | -0.4701 | -0.6318 | 0.3329 | 0.0363 | -0.0532 |
| dclub ($x_{7t}$) | 0.215 | 0.618 | 0.0457 | -0.3433 | 0.6571 | -0.1356 | -0.0415 | 0.0055 |
| dunion 9 ($x_{8t}$) | 0.0814 | 0.1782 | 0.8237 | 0.5273 | 0.0348 | 0.0573 | -0.0185 | -0.0132 |

Notes: dhelp presents 'receiving help from others', dsupport presents 'having someone to lean on', dtrust presents 'does not feel lonely', dfriends presents 'having a lot of friends', dfreq presents 'frequent contacts', dcommunity presents 'feeling part of the local community', dclub presents 'active member of a club or association' and dunion presents 'union membership'.

Table A4 shows the correlation between the variables used in the PCA, which verifies that the components of the PCA are sufficiently different from one another to relate to various dimensions of social capital. The eigenvalues and the cumulative proportion as shown in Table A5 indicate the variation that is accounted for from the 8 variables chosen. As we can see, the first component accounts for 26 per cent of the variation in the data. Since this is relatively low, a number of other variables should be chosen. Although there is no consensus on how many and which components should be considered, it is argued that those components with eigenvalues greater than one have a larger variation than the variance of the individual standardized $x_{it}$ variables (Manly, 2004). The first three components seem to be more important as they seem to have a larger variation and are all greater than one.

Table A6 reports the eigenvectors obtained which present the coefficients of the principal components at time $t$.[21] It is noticeable that the $PC_{2t}$ and $PC_{3t}$ seem to contain more relevant information where the $PC_{2t}$ is led by dcommunity and dclub (coefficients $x_{6t}$ and $x_{7t}$), while $PC_{3t}$ is led by dunion (coefficient $x_{8t}$). In order to investigate which principal component is most suitable for the analysis and whether

[21] Note that this presents the principal components taken as an average over the 11 year period to illustrate an example on how the PCA index was created. In order to construct the PCA variable for the analysis, the principal components of each year have been captured and merged in order to capture each variation in the data for every wave, rather than the average.

$PC_{2t}$ and $PC_{3t}$ are more relevant, the regressions have been re-estimated using all three components as well as each of the three at a time. However, since no effect is observed, the analysis has been conducted using the first principal component.

The first principal component used as a proxy for social capital can be represented as the following regression:

$PC_{1t}$=0.4376$x_{1t}$ + 0.4679$x_{2t}$ + 0.4618$x_{3t}$ + 0.3843$x_{4t}$ + 0.2885 $x_{5t}$+ 0.3043$x_{6t}$+ 0.215$x_{7t}$ + 0.0814$x_{8t}$,

where the first principal component $PC_{1t}$ is a function of 8 eigenvectors (its coefficients).